Mobilization or Intimidation? The Effect of Police Shootings on Voter Turnout

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Abstract

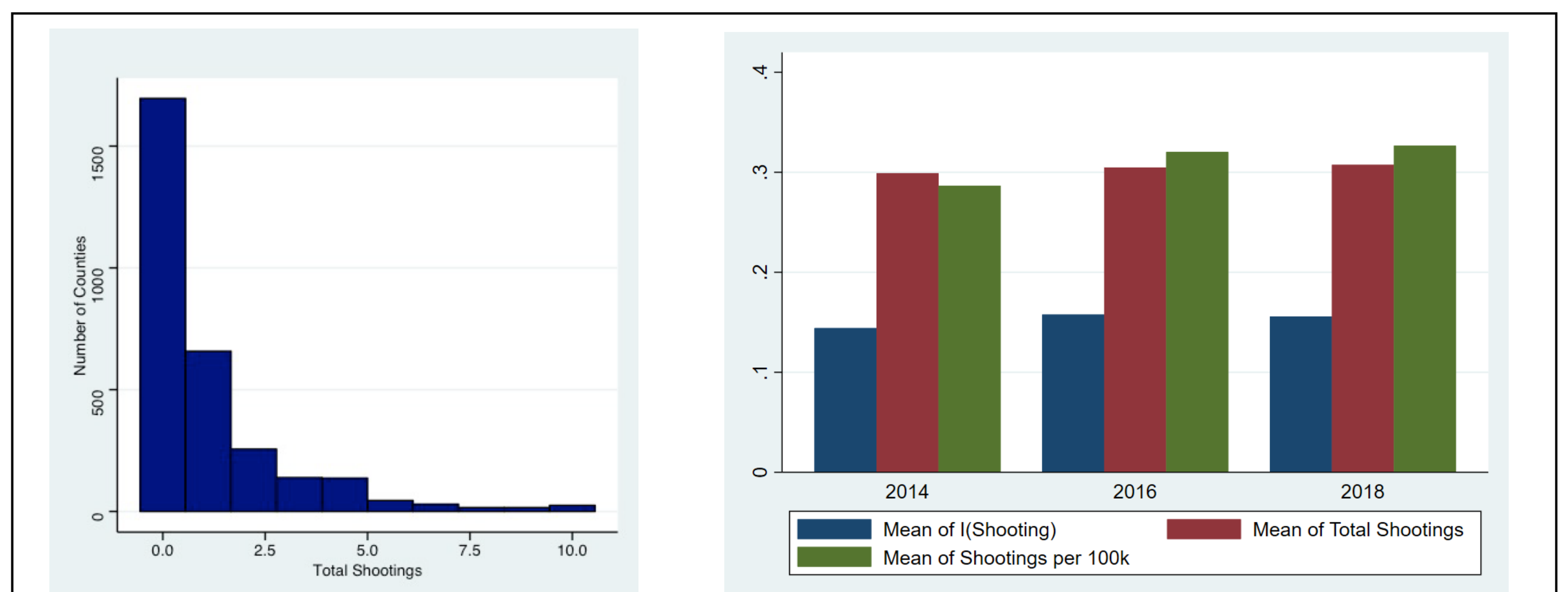
This paper examines the impact of police shootings on voter turnout. Specifically, I ask whether police shootings in the United States during the period leading up to the midterm 2014 and 2018 elections as well as the 2016 presidential election has a relationship with voter turnout at the county level. Only one notable study examines the impact of a specific policing policy (Stop, Question, and Frisk) on voter turnout in the state of New York. To this point, no studies have directly examined the relationship between police shootings and voter turnout. I test this link using a county and year fixed-effects model. I find that there is the possibility of either no effect or multiple mechanisms pushing results in opposite directions, both of which are possible and indistinguishable in my study.

Introduction

Is voter turnout a problem? In the United States, the population of voters is not necessarily representative of the whole population. Thus, for the democracy to fully serve all citizens, more participation is preferred. The United States also has particularly high rates of police shootings, especially compared to other OECD countries. Is there a relationship between police shootings and voter turnout by county in the United States in the past 3 election cycles?

According to Downs, individuals act rationally by considering the costs and benefits of voting. Many have linked demographics such as education, income, race, age, gender, marital status to voter turnout. Also relevant is the trust a citizen has in their government. In the more directly related context of New York City, a study examined the impact of the Stop, Question, and Frisk (SQF) program on voter participation. Finally, while less directly related to the implications of police violence in the United States, studies from other countries help to fill in the overall picture of state violence and voter turnout. In underdeveloped countries, democracy tends to be less stable and there are more overt uses of violence.

With this information in mind, I compile county-level data on police shootings (Mapping Police Violence), voter turnout (Dave Leip's Atlas of U.S. Presidential Elections), and demographic, economic, and crime controls.



Left: Distribution of Shootings per County; Right: Time Trends in Shooting Variables

Methodology

For this analysis, I use two types of models: an ordinary least squares model specified for each of the three election cycles, and a fixed effects model specified using only the 2014 and 2018 midterm election cycles. Additionally, for all models, I examine a 3-month and a 10-month period of police shootings, both periods ending on the election day for each year. For example, the 2014 3-month period begins on August 4th, 2014 and ends on November 4th, 2014. This allows me to examine whether the immediacy of the shooting is important to the effect on turnout. The turnout as a percentage of the total population in county i in election cycle t is explained by the number of police shootings per 100,000 residents in county i in election cycle t for the window w. The additional vectors represent economic and demographic controls and county and year fixed effects.

$$Vote_{i,t} = \beta_0 + \beta_1 Shootings_{i,t-w} + \beta_2 I(Presidential) + \beta_3[Shootings_{i,t-w}\ X\ I(Presidential)] + \boldsymbol{\lambda_e} + \boldsymbol{\lambda_d} + \boldsymbol{\gamma_c} + \boldsymbol{\gamma_y} + \varepsilon_{i,t-w}$$

Results

Table 1: Regression Results for Midterm Cycles

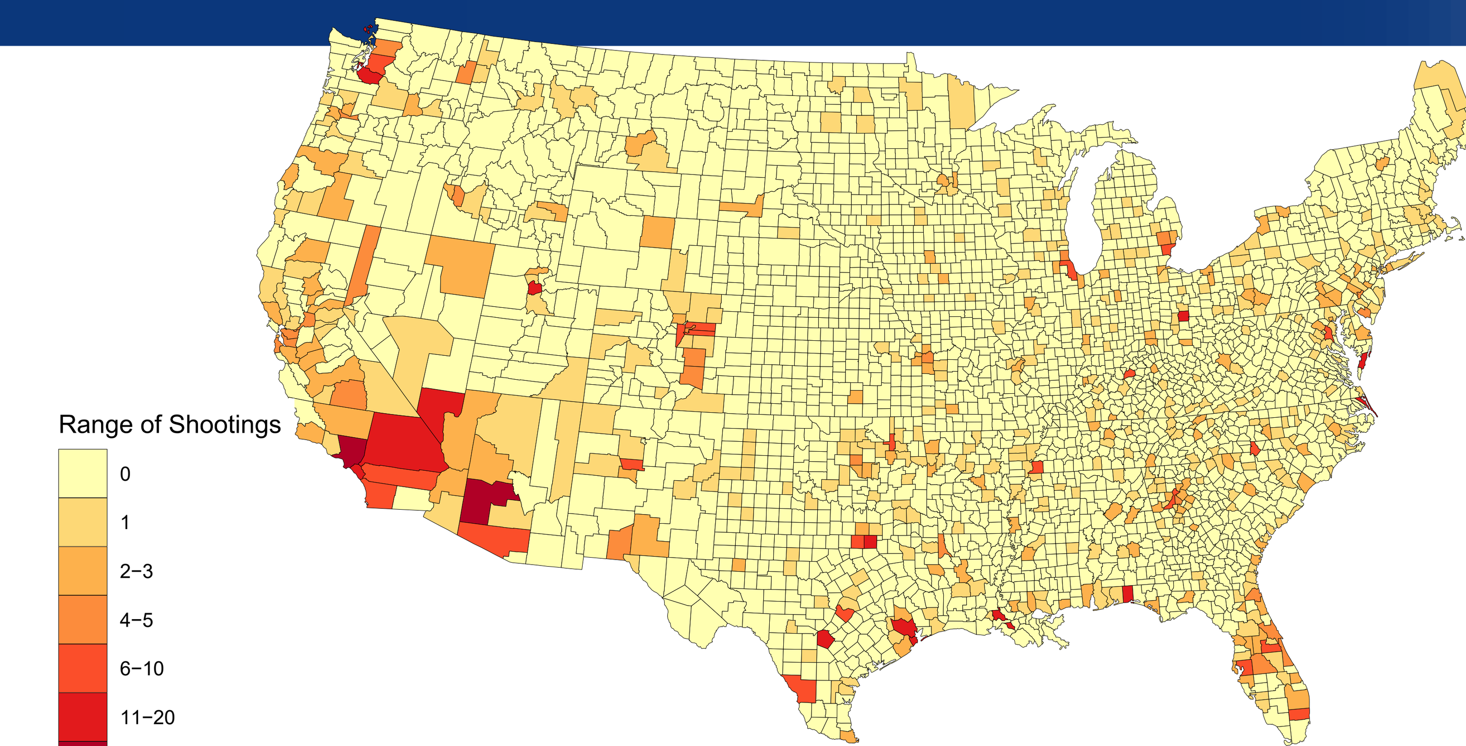
	3 Month Window				10 Month Window			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout
Shootings per 100k	-0.201***	-0.0384	-0.142*	-0.0407	0.0581	-0.00480	-0.0190	-0.0240
	(0.0656)	(0.0586)	(0.0837)	(0.0701)	(0.0812)	(0.0485)	(0.0715)	(0.0418)
			(3.849)	(3.690)			(3.851)	(3.689)
Violent Crimes Per 100k			0.00215	0.000501			0.00210	0.000401
			(0.00134)	(0.00122)			(0.00133)	(0.00122)
Property Crimes Per 100k			-0.00136***	-0.000915***			-0.00137***	-0.000920***
			(0.000402)	(0.000345)			(0.000401)	(0.000346)
			(0.0651)	(0.0618)			(0.0647)	(0.0615)
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	N	Y	N	Y
Demographic Controls	N	N	Y	Y	N	N	Y	Y
Economic Controls	N	N	Y	Y	N	N	Y	Y
Constant	33.17***	29.01***	25.58	25.05	33.15***	29.01***	31.09	30.80
	(0.00527)	(0.0454)	(29.01)	(27.03)	(0.0249)	(0.0470)	(29.05)	(26.98)
Observations	6,180	6,180	4,905	4,905	6,213	6,213	4,930	4,930
R-squared	0.001	0.733	0.748	0.773	0.000	0.733	0.749	0.773
Number of FIPS	3,107	3,107	2,747	2,747	3,107	3,107	2,748	2,748

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Regression Results Including All Election Cycles

	3 Month Window					10 Month Window				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout	Turnout
Shootings per 100k	0.0324	-0.0394	-0.0746*	-0.0412	-0.00741	0.0577	0.00487	0.00783	-0.0130	0.00596
	(0.146)	(0.0332)	(0.0396)	(0.0341)	(0.0478)	(0.0677)	(0.0273)	(0.0490)	(0.0265)	(0.0332)
2016 X Shootings per 100k					-0.0772					-0.0618
					(0.0658)					(0.0491)
Violent Crimes per 100k			0.00112	-0.000217	-0.000220			0.00111	-0.000230	-0.000213
			(0.00123)	(0.000992)	(0.000991)			(0.00123)	(0.000992)	(0.000992)
Property Crimes per 100k			-0.00141***	-0.000865***	-0.000871***			-0.00142***	-0.000861***	-0.000875***
			(0.000310)	(0.000250)	(0.000251)			(0.000309)	(0.000250)	(0.000251)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	Y	N	Y	Y	N	Y	N	Y	Y
Demographic Controls	N	N	Y	Y	Y	N	N	Y	Y	Y
Economic Controls	N	N	Y	Y	Y	N	N	Y	Y	Y
Constant	37.00***	29.01***	142.1***	120.2***	119.7***	36.98***	29.01***	141.4***	120.2***	120.0***
	(0.0134)	(0.0570)	(29.25)	(25.80)	(25.86)	(0.0211)	(0.0574)	(29.40)	(25.86)	(25.88)
Observations	9,320	9,320	7,494	7,494	7,494	9,320	9,320	7,494	7,494	7,494
R-squared	0.000	0.851	0.871	0.896	0.896	0.000	0.851	0.871	0.896	0.896
Number of FIPS	3,108	3,108	2,806	2,806	2,806	3,108	3,108	2,806	2,806	2,806

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1



2018 Police Shootings Geographic Variation

Discussion & Conclusion

It is imperative to understand the determinants of voter participation in the United States to ensure the success of the democracy. My study set out to examine the relationship between police shootings and voter turnout in the United States. I leveraged a nascent dataset on police shootings from Mapping Police Violence in combination with county-level voting data to create simple OLS analyses as well as fixed-effects analyses. I found a small negative effect of the number of shootings per 100,000 residents in a county on voter turnout, but the effect was economically miniscule, especially compared to other determinants of voting behavior. Police violence has received more and more news coverage and therefore there may be changes in attitudes between the years of my study. Finally, there are different candidates and different political platforms set forth in each election which is not accounted for in my model specifications. The effect of police violence could still be mixed with a positive effect in some cases and a negative effect in others. An example of a negative force could be that police shootings reduce the amount of trust a citizen has in the government, thereby decreasing voter turnout.

Selected References

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